Quest Journals
Journal of Software Engineering and Simulation
Volume 9 ~ Issue 2 (2023) pp: 23-34
ISSN(Online) :2321-3795 ISSN (Print):2321-3809
www.questjournals.org

Research Paper

Context of Medical Information Processing System Using Deep Learning and Natural Language Processing

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Abstract
This paper aims to develop and analyze deep learning and natural language processing systems in the context of medical information processing. The amount of data created about patients in the healthcare system is always increasing. The human review of this enormous volume of data derived from numerous sources is expensive and takes a lot of time. Additionally, during a patient visit, doctors write down the patient's medical encounter and send it to nurses and other medical departments for processing. Often, the doctor doesn't have enough time to record every observation made while examining the patient and asking about their medical history which takes time for a medical diagnosis to be made. The manual review of this vast amount of data generated from multiple sources is costly and very time-consuming. It brings huge challenges while attempting to review this data meaningfully. Therefore, the goal of this research is to create a system that will address the aforementioned issues. The suggested method extracts voice data from medical encounters and converts it to text using Deep Learning (DL) and Natural Language Processing (NLP) techniques. More so, the system developed will improve medical intelligence processing by using deep learning to analyze medical datasets and produce results of a diagnosis, assisting medical professionals at various levels in making realistic, intelligent decisions in real-time regarding crucial health issues. The system was designed using the Object-Oriented Analysis and Design Methodology (OOADM), and the user interfaces were put into place utilizing Natural Language Processing techniques, particularly speech recognition and natural language comprehension. Speech recognition allows for the taking of free text notes, which can drastically cut down on the amount of time medical staff spends on labor-in the tensive clinical recording. By extracting different pieces of data for medical diagnosis and producing results in a matter of seconds, a deep learning algorithm demonstrates a significant capacity to construct clinical decision support systems. The system's results demonstrate that the deep learning algorithm enabled medical intelligence to be 96.7 percent accurate.

Keyword*: Deep Learning, Machine Learning, Medical Information System, NLP*

Received 08 Feb., 2023; Revised 18 Feb., 2023; Accepted 20 Feb., 2023 © The author(s) 2023. Published with open access at www.questjournals.org

I. INTRODUCTION

To generate and deliver services to patients, all actions and activities carried out in the healthcare industry are combined into medical information processes. Given the significance of medical information processing, attempts to enhance procedures can significantly affect the performance of the industry, boosting efficiency, decreasing time wasted, and opening up prospects for income generation, especially in developing nations like Nigeria. When we look at the healthcare industry, we see that the availability of electronic health records in healthcare facilities produces a ton of data that is very beneficial for performing clinical research. Electronic health record (EHR) systems have become widely employed in hospitals and clinics during the past few years. The analysis of this enormous amount of data will lay the groundwork for better patient care. However, it is expensive and takes a lot of time to manually review this enormous amount of data that was created from many sources. When attempting to review this data meaningfully, it poses enormous obstacles. In underdeveloped nations like Nigeria, doctors document patient visits on paper and pass them along to nurses and other medical departments for processing. These documents, which are used to process medical data for the healthcare industry, must be error-free. In hospitals, patient record errors are a major issue. During a patient visit, 81 percent of doctors did not have access to all the information they needed, according to observational research done in a university clinic (Tang, 2014).

As a result, artificial intelligence (AI) tools are playing an increasingly significant role in improving clinical research and care. Natural Language Processing (NLP) and Deep Learning (DL) approaches have been used to extract information from various EHR that are locked in clinical narratives. While reinforcement learning techniques can be utilized in the context of robotics-assisted operations, computer vision techniques can be used for medical imaging, and NLP can be used to analyze unstructured data in the EHR. While evaluating text and figuring out the grammatical relationships between phrases, NLP algorithms can be utilized to find clinically relevant phenotypes. The identification of a significant portion of real cases and a high positive predictive value in clinical records can be achieved using rule-based NLP approaches.

The goal of natural language processing (NLP) is to infer meaning from words by analyzing speech and text. Deep learning methods called recurrent neural networks (RNNs) are essential for processing sequential inputs including language, voice, and time-series data (Esteva, 2019). Deep learning is a kind of machine learning that can create unsupervised models from unlabeled or unstructured data. On the other hand, deep learning will be able to automatically extract the best features from the data that is provided. The practice of utilizing computer algorithms to recognize essential components of a common language and extract meaning from unstructured spoken or written data is known as natural language processing. Artificial intelligence, computational linguistics, and other machine learning fields are needed for NLP (Bresnick, 2020). To categorize patients into a subgroup according to rules and learners, NLP algorithms first extract information or concepts from EHRs, then analyze extracted information. Deep Learning and NLP's Place in Healthcare Basically, we may group the users of the healthcare information originating from the following four sources:

1. Doctors
2. Patient;
3. Medical assistants
4. Pharmaceuticals

The diagnosis of an illness determines the course of every post-process. A person can receive the appropriate treatment if the ailment is correctly identified. Due to delays in decision-making, patient situations can occasionally become dangerous. A large-scale network that will accept a range of input data kinds, such as text, image, audio, time-series data, etc., is going to employ deep learning to acquire useful features for each data type in its lower-level towers. The Deep Neural Network is then able to draw conclusions based on reasoning and evidence from various sorts of data as the data from each pillar is combined and passes through higher layers. Information extraction, unstructured data to structured data conversion, document categorization, and summarizing are all areas where natural language processing can benefit the healthcare industry. Through correct prior authorization approval and effective billing, it will ultimately lower administrative costs. Additionally, it will add medical value by supporting poor clinical judgment, streamlining the evaluation of medical policy, etc (Rangasamy, 2018). In addition, it will enhance patient contact with healthcare professionals and electronic health records (EHR), raise patient health awareness, enhance the standard of care, and identify individuals who require urgent medical attention. Therefore, the goal of this research is to create a system that doctors may use to document the patient's medical inquiries while they are there. As the doctor speaks the prescriptions, natural language processing converts them to text and stores them in the database. Additionally, this will be web-based and coupled with an electronic health record, making it mobile-friendly.

Natural Language Processing in Intelligent Healthcare

A healthcare system is known as "smart healthcare" makes use of cutting-edge technologies like artificial intelligence (AI), blockchains, big data, cloud/edge computing, and the internet of things (IOTIoTo create a variety of intelligent systems that connect healthcare participants and improve healthcare quality (Tian, 2019). The public, healthcare service providers and third-party healthcare participants are the three main groups of participants in smart healthcare. Representative smart healthcare scenarios peraboute participants include smart homes, smart hospitals, intelligent life science research and development, health management, public health, rehabilitative therapy, etc. The main players, cutting-edge technology, and illustrative scenarios of smart healthcare are shown in Figure 3.

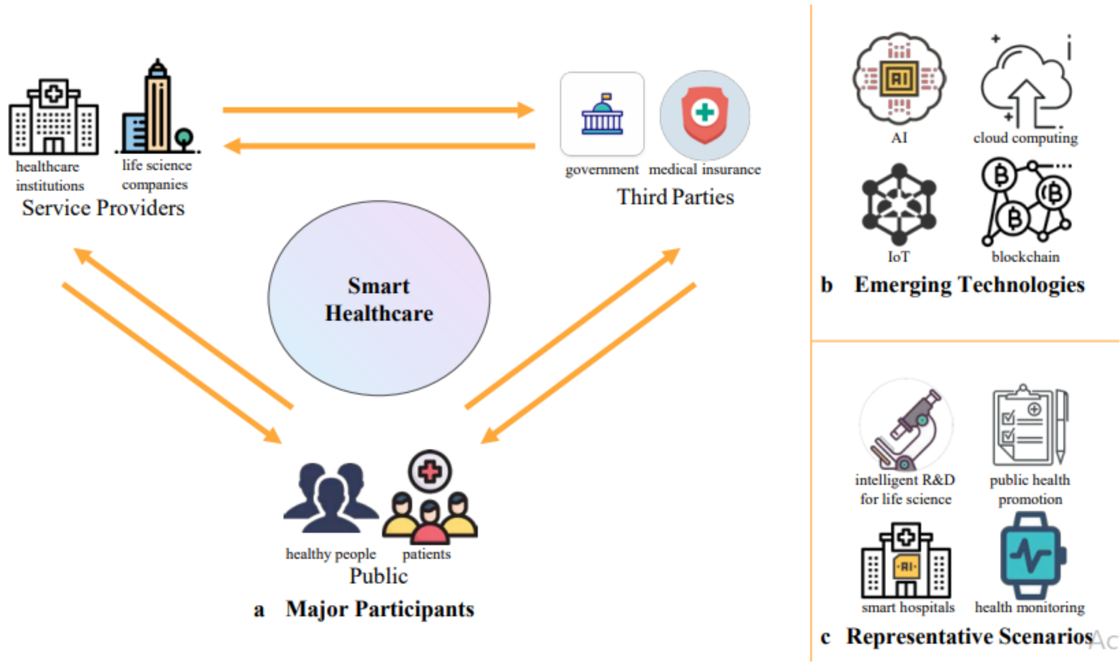

Figure 1: Intelligent healthcare (Tian, 2019)

The public, healthcare service providers and third-party healthcare participants are the main stakeholders in smart healthcare, as shown in Figure 1a. Figure 1b shows how cutting-edge technology like artificial intelligence, block chains, cloud computing, the internet of things, and others enable smart healthcare applications. Figure 1c shows an example of a smart healthcare scenario, which also includes intelligent research and development for life science, the promotion of public health, smart hospitals, health monitoring, and other things. Computer science and artificial intelligence's field of natural language processing (NLP) is concerned with the automatic analysis, representation, and comprehension of human language (Young, 2018).

Deep Learning

Artificial neural networks are used in deep learning to carry out complex calculations on vast volumes of data. It is a form of artificial intelligence that is based on how the human brain is organized and functions. Machines are trained using deep learning algorithms by learning from examples. While self-learning representations are a hallmark of deep learning algorithms, they also rely on ANNs that simulate how the brain processes information. To extract features, classify objects, and identify relevant data patterns, algorithms exploit unknown elements in the input distribution throughout the training phase. This takes place on several levels, employing the algorithms to create the models, much like training machines to learn for themselves. Artificial neurons sometimes referred to as nodes, make up a neural network (figure 2), which is arranged similarly to the way the human brain does. Three layers of these nodes are layered atop one another (Avijeet, 2022):

The input layer
The hidden layer(s)
The output layer

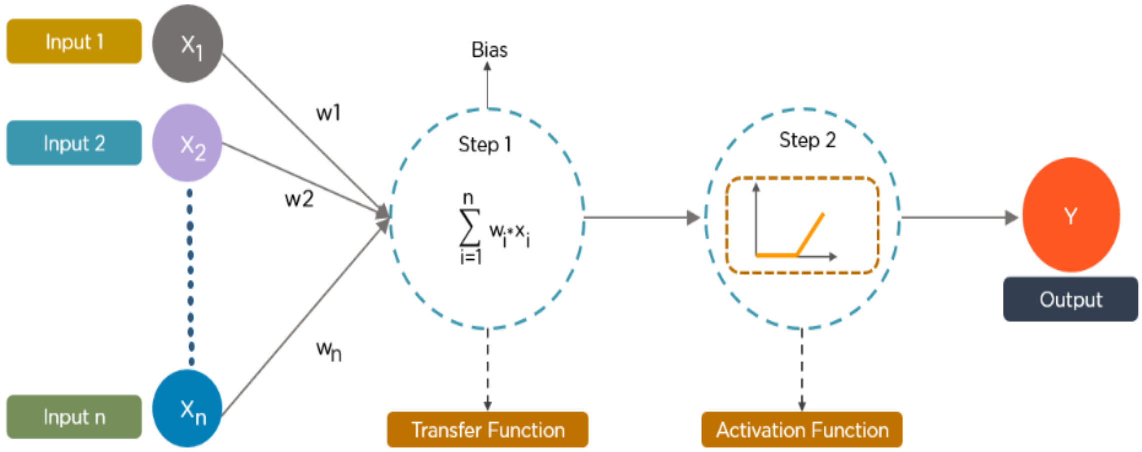

Figure 2: ANN Structure

Each node receives information from data in the form of inputs. The node calculates the inputs, multiplies those using random weights, and then adds a bias. To choose which neuron to fire, nonlinear functions—also referred to as activation functions—are used. Convolutional neural networks (CNNs), long short-term memory networks (LSTMs), recurrent neural networks (RNNs), generative adversarial networks (GANs), radial basis function networks (RBFNs), multilayer perceptrons (MLPs), self-organizing maps (SOMs), deep belief networks (DBNs), restricted Boltzmann machines (RBMs), autoencoders, etc. are some of the algorithms used by deep learning models. No network is seen to be flawless, although some algorithms are better adapted to carry out particular tasks. The Long Short Term Memory Networks (LSTMs) technique will be used in this paper.

1. Related Works on Medical Information System

Natural language processing research was presented by Binggui *et al*. (2022). They believe that artificial intelligence (AI) technologies provide a wide range of intelligent applications in a variety of healthcare contexts. From a technological standpoint, they concentrated on feature extraction and modeling for various NLP tasks seen in smart healthcare. The elaboration mainly focuses on typical smart healthcare situations, such as clinical practice, hospital management, personal care, public health, and drug research, in the context of NLP-based smart healthcare apps. They were able to demonstrate the power and potential of NLP for providing smart healthcare through the system they designed. They go on to explore the shortcomings of recent research in the areas of interpretability, human language understanding, and the use of NLP systems for smart healthcare. Finally, they suggested integrating multimodal and longitudinal data, creating end-to-end apps, few-shot learning, and merging several NLP algorithms (Binggui *et al*., 2022). According to Miguel *et al*. (2021), radiology reports are papers that describe and interpret ultrasound pictures. If done correctly, the computerized processing of these texts can aid in the diagnosis of medical practitioners. Regarding the case study of the work, it is impressive that the odd findings were correctly detected because they could have an impact on the patient's health. Focusing on challenging instances can also benefit scholars and medical professionals. In the outpatient healthcare setting Daryl *et al*. (2015) created an android application for an electronic medical record system. The design and implementation of a suggested outpatient management system that enables effective administration of a patient's medical information were given in the study. By fusing a chosen open source EMR system with a proposed Android-based mobile application, they offered a system for scheduling appointments with medical professionals.

With the help of the application, patients and doctors may schedule appointments and use the electronic messaging feature to instantly send reminders as the appointment time approaches. Before the suggested system is implemented in the public health care system, several constraints of the system prototype, such as user authentication and data security, must be effectively addressed (Daryl et al. 2015). Pedro (2019) stated that enterprises should employ use cases for chatbots because of how users are using chat platforms and advances in natural language comprehension. To prioritize the more suitable use cases among a range of prospective use cases for Chatbot implementation, a use case selection method was developed. This technique makes use of the factors acquired. According to Gaurav (2019), free-text allows clinicians to record detailed information about patients in narratives and first-person accounts. By developing and analyzing prototype systems for both clinical care and research applications, he illustrates this strategy in his dissertation. He created an interactive platform that allows clinicians to train and create binary NLP models independently for the PTO review procedure notes in the past. The outcomes of the creation and assessment of these prototypes will offer perception into the generalized design of interactive NLP systems for more extensive clinical applications (Gaurav, 2019).

According to Sarmad (2020), a Medicare system that serves as a kind of medical social media is being developed. The article created the Medicare system to utilize strategies including social networking sites, smartphones, wearable technology, and medical equipment to improve the quality of healthcare in Iraq. Through its Android App Interface, the Medicare system is accessible on Android-powered tablets and smartphones. Additionally, electronic devices such as PCs, cellphones, and tablets can use the Medicare web application. Only a few categories of research have been done on a system like the one that is proposed that is aimed at the Iraqi environment, especially those from rural areas who cannot receive health services via the Internet, and the current effort seeks to address this gap (Sarmad, 2020). According to Deepa (2012)'s research, the adoption of smartphones and tablets has inspired a lot of curiosity among healthcare professionals. A growing number of medical institutions have started developing courses for smartphones and tablets. By removing the need to be tied to a workstation, a portable tablet that makes clinical documentation easier can increase the mobility of residents and doctors. A clinical evaluation tool for syncope was created on an iPad to test its usability in this setting given the popularity of Apple's tablet computer. The main goal of the thesis was to create and evaluate mobile tablet software for clinical evaluation. The app's information is based on clinical practice recommendations. Using organized, prepopulated items and unstructured free-text narratives, the app support clinical evaluation. The study demonstrated that an app with a focus on usability during design and development may be created using evidence (Deepa, 2012). According to Sabina (2013), the use of wireless networks and mobile applications is expanding quickly across a variety of global industries. The researcher has provided a comprehensive architecture for a secure mobile healthcare system in the thesis. The maintenance of patient medical records in a local setting is provided by this application. The Android platform was used to create the mobile application. Because it satisfies crucial security needs, such as integrity, confidentiality, and availability, this solution is sufficiently safe. The researcher proposed that the same mobile application that was put into use may be improved with features for remote patient monitoring for the elderly or disabled. In that circumstance, patient data should be gathered via wireless sensor devices. The patient's mobile phone can then get the data that was collected. After that, a mobile device can send data to a server for a healthcare database (Sabina, 2013).

According to Sumithra *et al*. (2018), during the past few years, there has been a growing understanding of the significance of using Natural Language Processing (NLP) techniques in clinical informatics research, which has resulted in revolutionary advancements. A special emphasis is focused on mental health research, a field that has received little attention from the clinical NLP research community but in which NLP techniques have significant application. Although there have been considerable recent improvements in clinical NLP method development, it was suggested that for the field to grow further, rigorous assessment needs to receive greater attention. According to Sumithra *et al*. (2018), the necessity of using Natural Language Processing (NLP) techniques in clinical informatics research has come to light more and more over the past few years, and this has resulted in revolutionary advancements. Research on mental health is given special attention because it is still largely understudied by the clinical NLP research community even though NLP techniques are very applicable in this field. Although recent developments in clinical NLP technique development have been noteworthy, they also suggested that for it to go further, more emphasis needs to be given to rigorous evaluation. In a paper, Ana (2016) discusses tools to support Process Discovery as well as approaches for the BPM life cycle phases of Process Identification, Process Discovery, and Process Analysis. The present study's findings were helpful for future work on extracting business process models from natural language literature (Ana, 2016).

According to Abu *et al*. (2012), "smartphones" are portable computing devices that can run third-party applications and have extensive mobile communications capabilities. Healthcare professionals are among the constantly expanding demographic of smartphone users. They wanted to categorize smartphone-based healthcare innovations that have been studied in academic literature according to their functions and to provide summaries of each category's publications. To find papers that explored the design, development, testing, or application of smartphone-based software for medical or nursing students, healthcare professionals, or patients, MEDLINE was searched. Many hospitals utilize a variety of paper forms to document their contacts with patients, according to Harrison *et al*. (2017); while these have been quite successful, the world is moving toward digitalization, necessitating the need for paperless medical records. A prototype web application system was developed and assessed for the client using the project management approach Scrum, which is backed by the workload measurement method NASA TLX and the usability evaluation method System Usability Scale (SUS). With the help of this technology, users may easily record measured health data on their smartphones in a very easy manner and monitor changes in their long-term health conditions. According to Nwabueze and Oju (2019), the usage of mobile healthcare applications has emerged as a key area of innovation that may help people manage their daily healthcare needs. In addition to helping people modify their behavior and prevent illness, mobile applications can help improve healthcare delivery, lower costs, and increase effectiveness. The article offers a prototype for an interactive mobile healthcare application that satisfies the demands of both patients and clinicians. For better healthcare services and delivery, the suggested mobile application would offer the best communication to nuseveralyers in the healthcare sector, including patients, physicians, and pharmacists.

2. Analysis of the New System

Figure 3 illustrates the user interface (UI) and backend of the proposed NLP-driven application. The backend receives text or speech input from the user via the user interface (UI), processes it using NLP models, and then returns the results to the user by offering certain services via the UI. Backend knowledge bases are also necessary for applications that primarily rely on knowledge. Through speech, writing, and other means, the UI enables information interaction, for improving the user experience with intelligent systems and accomplishing smart medical information processing, easily accessible user interfaces are essential. Utilizing NLP techniques, particularly speech recognition and natural language comprehension, one can develop such user interfaces. The fundamental design of NLP-driven applications is depicted in Figure 3.

Speech recognition can be used in the proposed system to take free text notes, which can cut down on the amount of time medical staff spends on the labor-intensive clinical recording. Additionally, the suggested system included clinical decision support (CDS) systems, which can offer doctors recommendations for diagnoses and treatments utilizing deep learning. Heart illness, often known as cardiovascular disease, will be the focus of the CDS (CVDs). The heart illness dataset (hears that log Cleveland and Hungary final) from kaggle.com/datasets will be used for deep learning (2022) between users and intelligent systems. The system was created with the utmost consideration for security, continuity, and accessibility of health information across space and time.

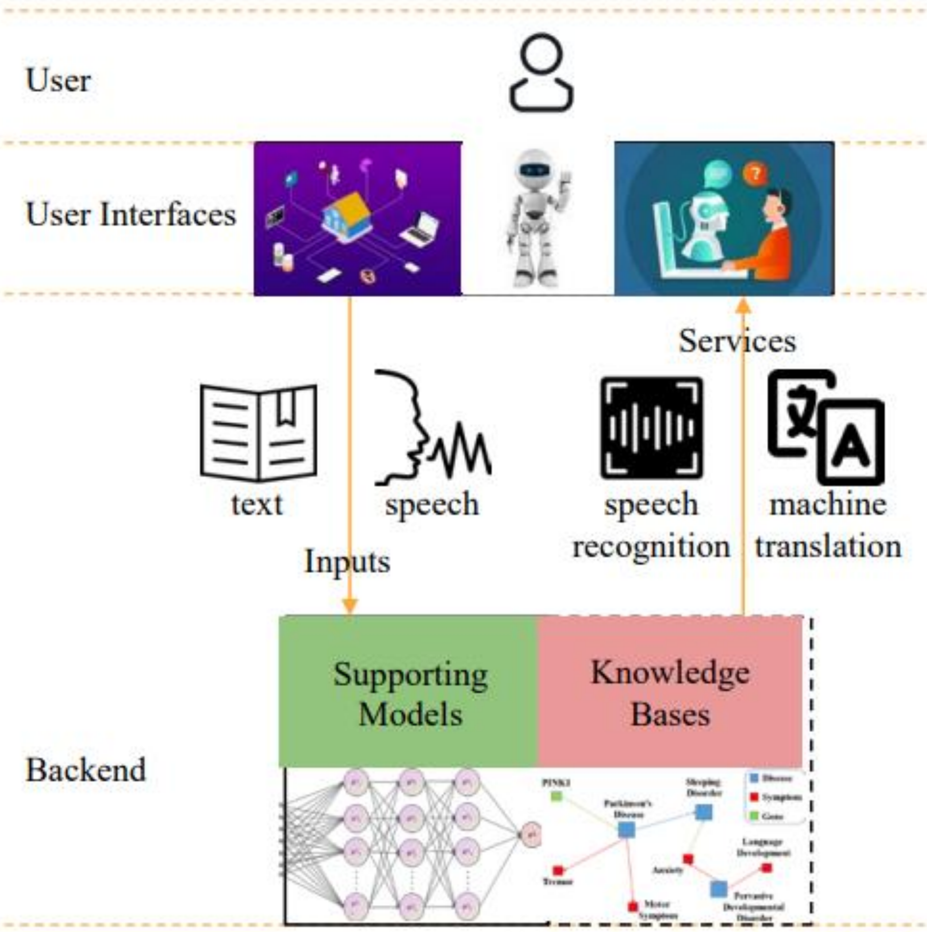

Figure 3 illustrates the fundamental design of NLP-driven apps.

Advantage of the Proposed System

The suggested system will have the following benefits:

1. Voice-to-text conversion that is automatic
2. The system would ensure real-time processing, analyzing, and accessing of data.
3. The system would include a convenient platform for communication between medical professionals and the general public.

4. The system would be knowledgeable, trustworthy, adaptive, adaptable, flexible, and agile.
5. The system would be reliable because it guarantees data security and those managers at all organizational levels (operational, tactical, or strategic) make wise, accurate, and timely medical decisions.

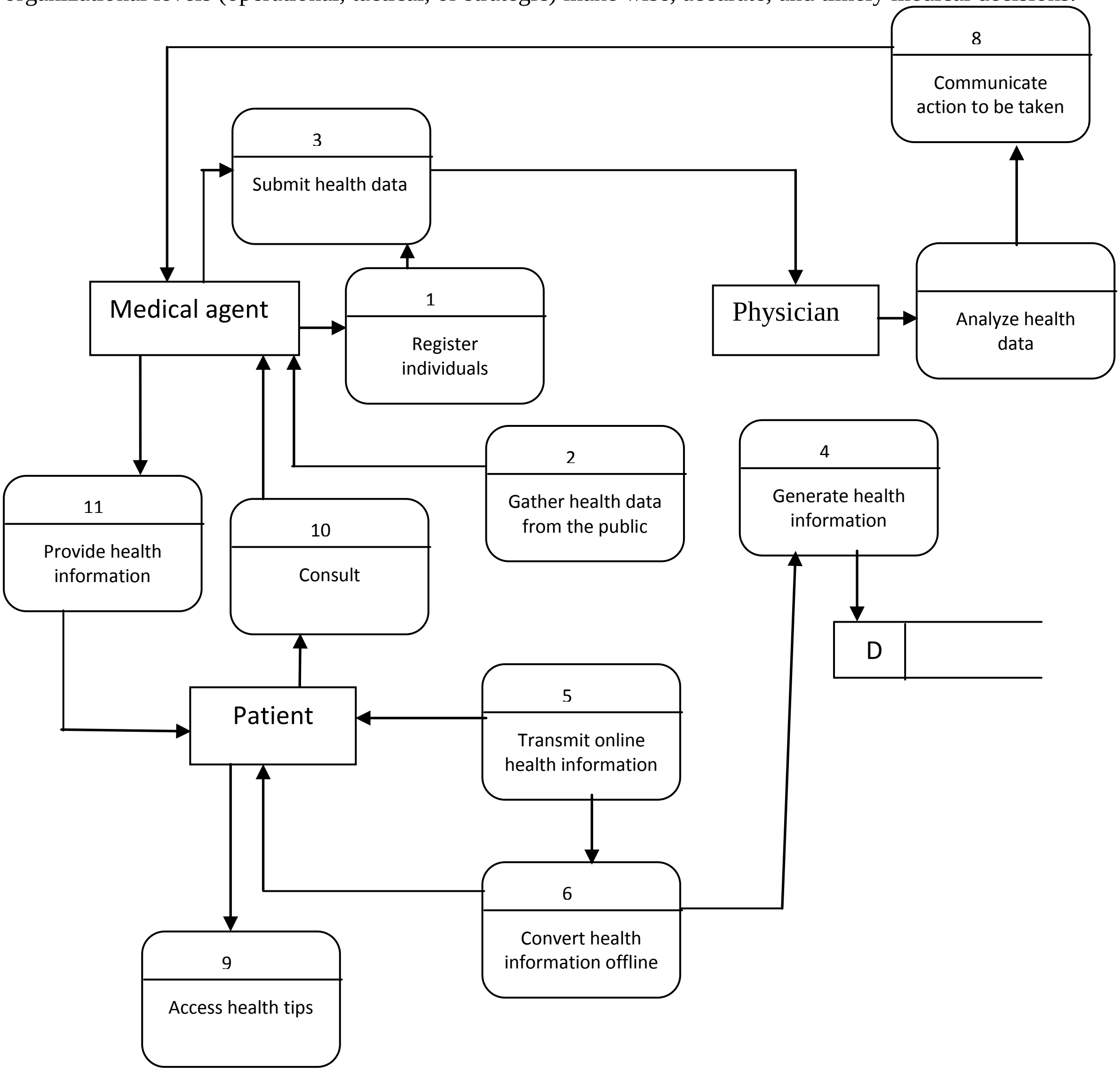

Figure 4: shows the proposed system's data flow diagram.

The health industry is in charge of the medical data from each data center, as shown in figure 4. The tertiary hospital, clinics, and community healthcare center make up each information integration platform, which enables the multiple levels of medical institutions in a region to share data from data centers and implement two-way referral and medical record lending.

3. Result and Discussion

This section describes the application's implementation and testing for problems and non-functional qualities including processing medical data securely, quickly, and robustly. To guarantee that the specified objectives have been accomplished correctly and the research questions have been addressed to produce a high-quality, user-friendly application, the test is simply the execution of the implemented application using sample data. The various modules of the application were tested, and some of those components are shown in figures 5, 6, 7,

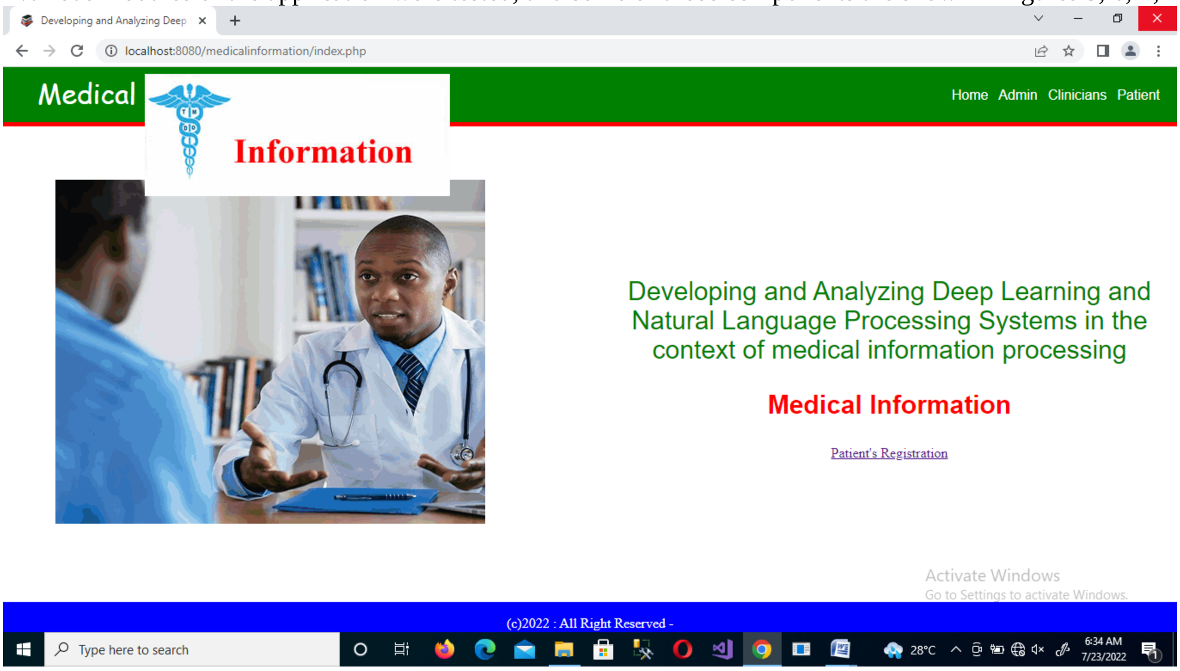

Figure 5: The main page for medical information processing

The application index page, shown in Figure 5, is the first screen you see when the Medical Information Processing platform is launched. Users can use this interface to access the login form.

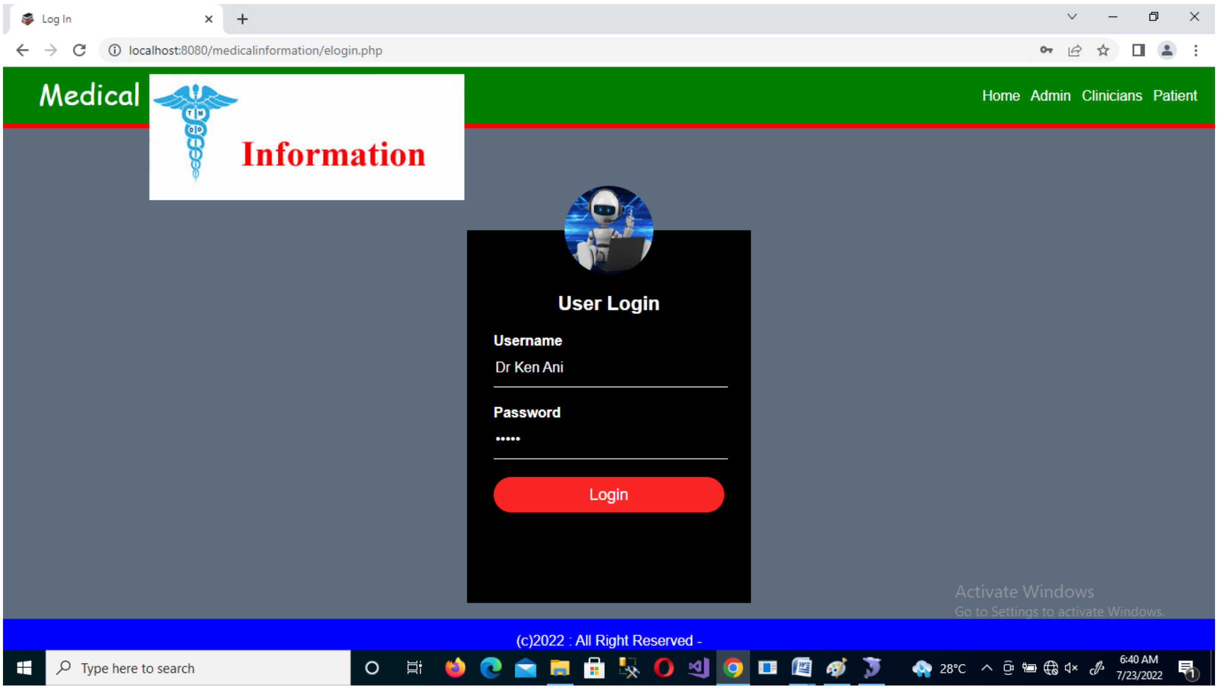

Figure 6: Login page

The initial security authentication for each user on the platform is shown in Figure 6. The username and password must be supplied by the user for authentication. At this point, the system checks the password entered by the user and disables access if the password doesn't pass the authentication test.

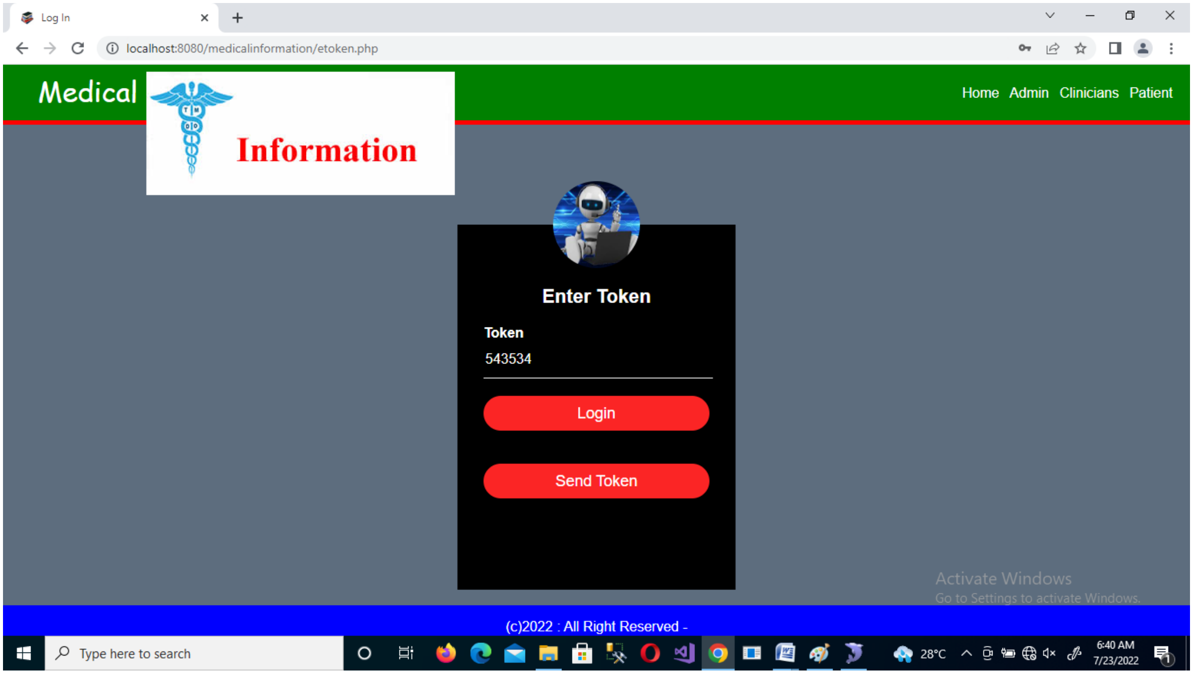

Figure 7: Token Verification page

The second security authentication for each user on the platform is shown in Figure 7. To authenticate the token, the user must provide the SMS receipt they got on their phone. The user will be able to choose options from the application menu after the token has been verified.

Evaluation

The software's performance was evaluated by classifying patient medical data gathered for a heart disease test quickly and accurately using deep learning. One of the largest heart disease datasets available for research purposes, the training data is derived from a dataset with 1191 records and 10 common attributes. The dataset uses the following features.The collection and production of a large amount of usable data by the medical information processing system allow for the measurement of numerous key performance indicators (KPIs) that support management in making decisions.

Table 1: Confusion Matrix

Observed

		True	**False**
Predicted	**True**	TP	FP
	False	FN	TN

$$AC = \frac{a+d}{a+b+c+d} \tag{1}$$

a = True Positive
b = False Positive
c = False Negative
d = True Negative

Thirty tests for heart disease were conducted as part of the testing to determine whether the system could correctly detect and categorize the patient as having heart disease or not using the data from the dataset and deep learning. The analysis of deep learning and natural language processing systems in the context of processing medical information is graded according to performance in Table 1.
Confusion matrix applied to test dataset in Table 1

Observed

		True	**False**
Predicted	**True**	12	1
	False	0	17

According to Table 1 of the 30 tests carried out using a deep learning system were True Positives and correctly predicted to have heart disease. 17 were identified as True Negatives, and it was properly predicted that they did not have heart disease. 1 displayed the incorrect categorization and was, therefore, a False Negative. As shown in equation 1, a model of performance measures may be generated from the confusion matrix, demonstrating the system's correctness.

With the numbers substituted, we obtain AC = (12+17) / (12+17+0+1) AC = 0.967, or 96.7 percent accuracy in predicting the result of the diagnostic of heart disease (see table 2).

Table 2: Performance Results Obtained

Technique Applied	Accuracy in classifying the Tickets
Deep Learning Algorithm	96.7%

II. Discussion

The goal of this research was to develop and analyze deep learning and natural language processing in the context of processing medical information. From the research done, it has been shown that the issues with medical information processing are more related to slow information retrieval and slow medical diagnosis and documentation. Therefore, the research project modeled a system that can convert voice to text during a medical contact using natural language processing. This was made possible by the software's ability to convert speech data from clinicians' observations made during a patient's medical examination into text using natural language processing. As a result, patient medical information is recorded more quickly and without delay. Additionally, the implementation of medical diagnostic for heart illness utilizing deep learning and heart disease dataset. The results of the implementation demonstrate that a patient can be classified as having a heart-related disease or not with an accuracy of 96.7%.

III. Conclusion

Providing high-quality healthcare is a challenging endeavor that is heavily reliant on patient data and medical expertise. As far as possible, decisions regarding a patient's care should be based on data from study rather than just clinical judgment and experience. Deep learning and natural language processing play a significant role in the analysis of medical data. It enables doctors to provide timely, high-quality care to their patients. Medical datasets provide historical data on health problems, diagnostic criteria, and treatment results. This will help the doctors learn from the many thousands of records in the collection. Learning cannot be done manually, but using a deep learning algorithm can make learning more efficient, accurate, and useful in clinical settings. Therefore, the system created by this research will help doctors handle medical information so they can provide patients with the high-quality, fast, and accurate care they need.

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